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Water as destiny – The long-term impacts of drought in sub-Saharan Africa

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ABSTRACT

We examine the long-term impacts of drought exposure on women born in 19 countries in sub-Saharan Africa, across four decades. We find that women who were exposed to drought conditions during their early childhood are significantly less wealthy as adults. These effects are confined to women born and raised in rural households, indicating that the impacts of rainfall are felt via changes in agricultural output. In addition to lower levels of wealth, women who experience droughts in infancy also receive fewer years of formal education and, in the case of extreme drought conditions, have reduced adult heights. Our results also suggest that drought exposure in infancy can have long-term, negative impacts on women's empowerment. Finally, we also show that these impacts may be transmitted to the women's offspring, with children of affected women more likely to be born at a low birth weight (weighing <2.5 kg). To our knowledge, this represents the largest study to date both geographically and over time showing a strong relationship between early life rainfall conditions and adult outcomes, and the first to show that the impacts could span generations.

1. Introduction

Can rainfall determine destiny? It has been well-documented that environmental conditions experienced in infancy can play a significant role in shaping adult outcomes. Numerous studies have shown a link between adverse conditions experienced during infancy, such as those caused by conflict, famine, and disease, and negative adult outcomes. In this paper, we examine the long-term impacts of periods of drought in early childhood on adult outcomes for women in sub-Saharan Africa. In rural areas, periods of extreme rainfall can have large impacts on agricultural output,[1] and thus, on income for the large proportion of households engaged in agricultural activities. This can lead to impacts on fetal and infantile development in several ways, including by impacting the health and stress levels of the pregnant or nursing mother, impacting the nutritional intake of either or both the pregnant mother and infant, or other impacts on human capital investment in the child. We ask whether droughts experienced in the early years of one's life, a critical period for human development, can lead to observable markers of reduced cognitive and physical development, and ultimately less wealth as an adult. As noted by Hoddinott and Kinsey (2001), wealthier and better educated women have healthier children. We therefore take this analysis one step further and test whether these events can cause impacts large enough to be passed on to a second generation.

In studies of early-life environmental shocks, much emphasis has been placed upon the effects of external conditions during early life – what is known as the *fetal origins hypothesis*. This research was pioneered by Barker (1990) who found that negative conditions experienced in utero may not manifest themselves until much later in life, potentially not until the affected child has reached middle age. While early research on the long-term impacts of infantile health (including the period in-utero) focused on health-related outcomes, more recently a relationship has been established between measures of health during early life and non-health outcomes. For example, Black, Devereux, and Salvanes (2007) find a significant relationship between birth weight (an indicator of fetal health), high-school graduation rates, IQ, and height. Almond and Mazumder (2011) find that mothers who fast during pregnancy (in observance of Ramadan) give birth to children who are more likely to be disabled as adults, and that

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[1] Econometric evidence that rainfall and temperature affect agricultural output goes back to Mendelsohn, Nordhaus and Shaw (1994).

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the impact is particularly large for learning disabilities.[2] Field, Robles, and Torero, (2009) find that the fetal origins hypothesis not only applies to negative nutritional conditions, but to positive ones too. Specifically, the authors find that iodine supplements taken during pregnancy have large positive effects on educational outcomes (although they find no impacts on health). An overview of the fetal origins hypothesis is provided by Almond and Currie (2011) and updated in Almond, Currie, and Duque (in press).

There also exists a well-established and growing literature linking climate to economic outcomes. Studies in this area have illustrated the impact of weather (typically focusing on rainfall and temperature) across a wide range of outcomes, including economic growth (e.g., Dell, Jones, & Olken, 2009, 2012), agricultural output (e.g., Auffhammer, Ramanathan, & Vincent, 2006; Deschênes and Greenstone, 2007; Mendelsohn, Nordhaus, & Shaw, 1994; Schlenker and Roberts, 2009), labor supply (e.g., Graff Zivin and Neidell, 2014), and health outcomes (e.g., Deschênes, Greenstone, & Guryan, 2009; Dinkelman, 2017; Grace, Davenport, Hanson, Funk, & Shukla, 2015). A detailed overview of this "climate-economy literature" is provided by Dell, Jones, and Olken, (2014). Studies in the climate-economy literature have taken both macro and micro perspectives. Our research focuses on the latter, examining the impact of extreme weather events (namely, droughts) on individuals. However, while many of the microeconomic analyses of climate focus on the contemporaneous impacts of extreme weather on individuals, we examine much longer-term effects. Thus, the present analysis seeks to contribute to the literature on the long-term impacts of climate on people.

There have, to date, been a number of analyses on the role that weather-related environmental conditions during a person's earliest years play in shaping later-life outcomes. For example, Alderman, Hoddinott, and Kinsey (2006) find that children in Tanzania who experienced malnutrition caused by civil war and drought were negatively impacted in terms of both height and educational attainment. Maccini and Yang (2009) find that the level of rainfall in infancy affects numerous later-life outcomes for women in Indonesia; specifically, that above-average rainfall in birth year is associated with improved health, educational attainment, and socio-economic status as an adult. Carrillo, Fishman, and Russ (2015) find that hotter temperatures while in-utero reduces adult income by between 1.1 and 1.7% in Ecuador. Studying the short- and long-term impacts of extreme rainfall shocks in Malawi, Abiona (2017) finds that children who experienced a dry rainfall period in their early life have lower weight-for-age and height-for-age z-scores later in childhood. Dinkelman (2017) estimates the impact of childhood drought exposure on long-term disability rates in South Africa and finds that drought exposure in childhood increases the rate of adult disability by 3.5–5.2 percent. Comfort (2016) finds that women who experienced high levels of rainfall while in utero had better pregnancy outcomes later in life. These results represent a pre-cursor to the intergenerational impacts that we explore in this research.

Analyses of the long-term impacts of environmental conditions, while important in and of themselves, are becoming more pertinent in light of the variability of environmental conditions caused by climate change. The impacts of climate change will not be evenly distributed across the globe, and while the more oft-cited impact is an increase in global temperatures, most climate models agree that climate change will result in an increased variability in rainfall patterns and in a more frequent occurrence of extreme rainfall events such as droughts and floods (Donat, Lowry, Alexander, O'Gorman, & Maher, 2016), and decreasing amounts of available water in local dry seasons (Kumar, Lawrence, Dirmeyer, & Sheffield, 2014). The impacts of such changes are likely to be most keenly felt in poorer regions, which both lack the infrastructure to protect against extreme events and the policies to effectively alleviate the impacts of water scarcity (Distefano & Kelly, 2017), as well as amongst households in rural areas that are highly dependent on rainfed agriculture as a source of income. As such, the effects of climate change are likely to have a large impact on rural households in sub-Saharan African – our current setting.

In this paper, we estimate the effect of environmental conditions during a child's earliest years on adult outcomes by exploiting exogenous deviations in rainfall from long run mean values within a local area.[3] Using the Standardized Precipitation Index (SPI) at the grid cell level, we define a drought as an SPI value that is -1.5 or lower; this provides a localized measure of drought that is consistent with the climatology literature. We also test more (SPI < -2) and less (SPI < -1) severe measures for drought. Using a rich set of fixed effects and controls, we conduct a quasi-natural experiment by comparing the adult outcomes of women who experienced extreme drought during early life with women born in the same region during times of normal rainfall levels.

There are many ways in which rainfall shocks experienced in infancy may impact adult wealth. For example, rainfall shocks may have a direct impact on infant health by altering the local disease environment. Poor infant health has also been shown to be related to altered socioeconomic conditions as an adult.[4] Furthermore, the impact on rural households—who depend on agricultural output as a major income source—is likely to be felt via altered economic conditions.[5] These possible pathways are summarized in Fig. 1.

The main model we estimate is a reduced-form approach that yields estimates of the overall long-term impact that drought in infancy has on adult wealth. To explore intermediate impacts, which may shed light on some of the pathways, we also examine the impact of drought on human capital, as measured by health (proxied by adult height) and educational attainment.

Testing for an effect of early-life drought on adult height may provide an indication of whether nutritional intake is an intermediate mechanism. In the developed world, linear growth (i.e., height) is generally viewed as a genetic endowment but, in the developing world where one in the three children under the age of five experience stunting (whereby they do not reach their genetic growth potential), it can be viewed as an outcome of early-life environment, such as nutritional intake, hygiene, and disease. Indeed, nutritional deprivation in a child's early years can lead to stunting,[6] and it has been shown that height at age three strongly predicts adult height (Hoddinott & Kinsey, 2001; Maccini & Yang, 2009). Beyond its use as a proxy for health, it has been shown that height itself may be significantly correlated with income.[7] This may be due to its links with cognitive development, social benefits such as increased self-esteem, or from the added productive capacity that comes with being taller and stronger, which may be particularly advantageous in rural settings.

[2] Looking at shorter term outcomes, Almond, Mazumder and Ewijk (2015) find that fasting during pregnancy also affects children's test scores in school.

[3] Our identification strategy is similar to that employed by Maccini and Yang (2009), Dell, Jones and Olken (2012), and Carrillo et al. (2015).

[4] Oreopoulos et al. (2008) find a relationship between infant health and educational attainment and welfare dependency as an adult, while Almond, Edlund and Zhang (2010) find that childhood exposure to famine impacts martial outcomes.

[5] It is also possible that the impact of drought on agricultural output could be felt in urban areas if the effect is large enough to cause an increase in food prices.

[6] The first 1000 days of life, from the beginning of pregnancy until age two, are generally viewed as the critical period in determining linear growth.

[7] This fact was noted over a century ago by Gowin (1917), more recently it has been verified by Case and Paxson (2008), Deaton and Arora (2009) and Vogl (2014) amongst others.

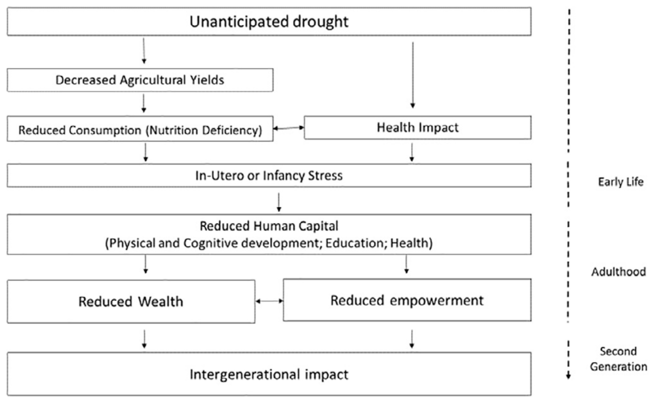

Fig. 1. Channels through which rainfall shocks can have long-term impacts *Notes:* Figure, adapted from Carrillo et al. (2015), shows the various pathways through which unanticipated droughts can have long run impacts.

Rainfall shocks in early childhood may also have effects via educational outcomes. The negative impact of in-utero nutritional deficiencies on later-life cognitive outcomes has been repeatedly found in empirical investigations of the fetal origins model (Hoek, Brown, & Susser, 1998; St. Clair et al., 2005; Currie, 2009). Thus, below-average rainfall may negatively affect the cognitive development of respondents through a nutritional deprivation channel, resulting in lower levels of education overall.[8] Given the strong relationship between education and wealth, this is an important potential channel linking early-life rainfall to adult wealth.

Our results show that periods of drought experienced in a child's earliest years, have significant long-term impacts, and that their effects are pervasive and long-lasting. We find that periods of drought are significantly associated with being less wealthy as an adult. Women who experienced droughts during significant shares of the first 5 years of their life achieved lower levels of educational attainment and grew up shorter. When we look at shorter time periods, for instance, examining rainfall in the year of birth only (Tables 5 and 6) or counting the number of monthly droughts (see Appendix 2), the impacts become weaker or insignificant. This may be evidence that families are able to smooth income to adapt to short-term droughts but are unable to when droughts persist for too long. Indeed, there is strong evidence from other studies that children can "catch-up" from stunting occurring in their first 6–18 months, and show no sign of reduced physical or cognitive function (Adair, 1999; Crookston et al., 2010; Golden, 1994). Thus, the longer time period we examine in our main specification may be warranted.

We also find that the impacts spillover into the behavioral domain, affecting female empowerment within the household. In addition to the moral dimension, female empowerment within the household has been shown to have positive implications for economic development (e.g. Duflo, 2012; Mehra, 1997). Finally, we find evidence that the impacts of drought in infancy can be carried over to the next generation. Our results show that the probability that a respondent has a child that is classified as being of low birth weight (born weighing <2.5 kg) is increasing in the fraction of her own childhood spent in severe drought conditions. This result suggests that the impacts of early-life rainfall shocks are strong enough to transmit the effects across generations.

This paper makes several distinct contributions to the literature on the long-term impacts of environmental conditions. Firstly, we focus on households in sub-Saharan Africa, where lower income levels make households particularly vulnerable to shocks. This is also a region that is vulnerable to the impacts of climate change – according to the Intergovernmental Panel on Climate Change, climate change is likely to exacerbate current conditions of water stress in much of Africa, and the interaction between rising temperatures and changes in rainfall patterns is likely to reduce crop productivity in the region (Intergovernmental Panel on Climate Change (IPCC), 2014). Furthermore, Barrios, Ouattara, and Strobl (2008) show that agriculture in sub-Saharan Africa is more vulnerable to climate change relative to other developing regions. The vulnerability of this region underscores the importance of the current analysis. Secondly, to the best of our knowledge, our analysis covers the widest sample both geographically and temporally ever studied in this literature, spanning 19 countries over 45 years. Finally, we consider a wide range of outcomes, and provide what we believe are the first set of results showing an intergenerational transmission of early-life rainfall shocks.

The paper proceeds as follows: Section 2 provides an overview of our data sources. Section 3 presents the methodology used in the analysis. Section 4 presents the results. Finally, in Section 5, we discuss the results and provide concluding remarks and some policy recommendations.

2. Data

We use two georeferenced datasets in this study: household surveys, to obtain birth records and outcome variables, and gridded weather data. The datasets are described below.

2.1. The Demographic and health survey

The main data source used in our analysis is the Demographic and Health Surveys (DHS). These are nationally-representative surveys that provide information on an extensive range of outcomes for women, and their households, in the developing world. We focus on rural households in sub-Saharan Africa, where the high reliance on rain-fed agriculture as a source of income heightens the vulnerability to rainfall shocks, although we do test for impacts in urban areas as well. The DHS program typically conducts surveys in each country every five-years, and we combine the data collected over time and across countries to form a pooled cross section. The specific questions posed in the DHS vary somewhat between countries and across survey years, thus our findings are based on a pooled cross-section of 25 surveys, covering 19 countries, where the availability of key information, such as geocoordinates and important indicators facilitate the empirical analysis. The countries, survey years, and the earliest and latest respondent birth year are listed in Table 1. Because the DHS focuses predominately on women, our analysis is restricted to female survey respondents. Whether this is likely to bias our results upwards or downwards is ambiguous; while Dinkelman (2017) and Abiona (2017) find that the long-term impacts of early-life rainfall shocks are greater for men than for women, other studies, for example Maccini and Yang (2009) and Carrillo et al. (2015) have shown that female children are more susceptible to early-life environmental shocks. Furthermore, Akresh, Verwimp, and Bundervoet, (2011) show that crop failure affects the health outcomes of girls in poor households, while boys in both poor and non-poor households are not impacted.

[8] Rainfall shocks later in childhood, which are not the focus of the current analysis, may also affect educational outcomes – via altered schooling decisions. However, the literature on their impact is ambiguous. Periods of low rainfall may mean children are not sent to school due to lower household income; Ferreira and Schady (2009) find that aggregate economic shocks have a negative impact on children's schooling in Africa. On the other hand, Shah and Steinberg (2017) find that it is above-average rainfall which negatively impacts education attainment, due to increased farm productivity which raises the opportunity cost of schooling for rural households, even for children as young as five.

Table 1
Data coverage – countries and time.

Country	Surveyed in:	Earliest birth year:	Latest birth year:
Burkina Faso	2003	1953	1988
Cameroon	2004	1954	1989
Congo (Democratic Rep.)	2007	1957	1992
Ghana	2003, 2008	1953	1993
Guinea	2005	1955	1990
Kenya	2003, 2008	1953	1993
Lesotho	2004, 2009	1955	1994
Madagascar	2008	1959	1993
Malawi	2004, 2010	1954	1995
Mali	2006	1956	1991
Namibia	2006	1957	1991
Niger	2006	1956	1991
Nigeria	2003, 2008	1953	1993
Senegal	2005	1955	1990
Sierra Leone	2008	1958	1993
Swaziland	2006	1956	1991
Uganda	2006	1956	1991
Zambia	2007, 2013	1957	1998
Zimbabwe	2005	1955	1990

Notes: Table shows the DHS surveys (country and year combinations) which are used in our analysis. Surveys were chosen based on three criteria: 1) Country must be in sub-Saharan Africa; 2) Survey must include geo-references of cluster enumeration areas; 3) Survey must include all critical questions needed for this analysis, including household wealth, maternal education and height, women's agency, children's birthweight, and an indicator of whether the respondent had migrated from their place of birth. Columns 3 and 4 show the earliest and latest years in which a surveyed woman was born.

From the DHS, we receive information on the year and month of birth of every adult female in each household, in total 236,820 women. However, we include only women who indicate that they have never migrated from their current location, leaving 106,330 women. This is necessary because while the location of the household is georeferenced, there is no survey question which asks the location of birth. Therefore, we can accurately match up early-life weather conditions for those who have not migrated. Of these non-migrant women, 76,914 are living in rural areas. There is birth weight information available for the children of approximately 14,000 rural, non-migrating women – it is for these children that we test for a potential intergenerational impact of drought.

The main outcome variable we consider is household wealth, as measured using the DHS wealth index score. The wealth index is a composite index of a household's living standards and as such is not calculated based on income, but rather based on the assets the household possesses, the materials from which their dwelling is constructed, and their access to water and sanitation. Using principal component analysis (by which various assets and facilities are assigned a weight), the DHS converts assets into a continuous wealth index variable.[9]

Beyond wealth, we also consider measures of human capital such as educational attainment and height; a measure of female empowerment; and the birth weight of the respondents' children (for those that have at least one child under the age of either three or five, depending on the DHS survey round). Educational attainment and height are continuous variables as recorded in the DHS data. Our measure of female empowerment is an indicator of whether the respondent reports that it is her husband or partner that has the sole say across a range of household decisions.[10] Finally, to examine the intergenerational impacts of rainfall shocks we looked at whether exposure to drought in early childhood is correlated with the likelihood of giving birth to a child that is of low birth weight. Following Grace et al. (2015), and Deschênes et al. (2009), we define a child as being low birth weight if they are born weighing <2.5 kg (approximately 5.5 lbs).

Our analysis focuses predominantly on the 73 percent of women in DHS surveys who are living in rural areas. Table 2 presents some descriptive statistics for these women. As Table 2 shows, the average respondent has completed approximately 3.6 years of schooling, with a median value of just two years. There are some extreme values for height in the data, thus in the empirical analysis, we remove outliers and focus on women who fall in or below the 95th percentile. For these women, the average height is 157.3 cm. The oldest respondent in our sample was born in 1953 while the youngest was born in 1998. Also notable are the low levels of female agency for the women in our sample, with more than half of the respondents reporting that their husband/partner has the sole say in any household decisions. Of the respondents for whom the data is available, approximately 14 percent have at least one child that was born weighing <2.5 kg.

2.2. Weather data

Historic weather data is from the University of Delaware's Global Land Temperature and Precipitation Data (Matsuura & Willmott, 2012a, 2012b), which provides monthly average data on rainfall and temperature at the 0.5 degree gridcell level (approximately 50 $\times$ 50 km at the equator). These gridded monthly temperature data are available from 1900 to 2013 and thus allow us to match outcome variables from the DHS with weather conditions at the time of birth using GPS coordinates of the household.[11] This dataset was specifically chosen for its long panel and wide coverage of sub-Saharan Africa over the study time period. It is one of the most commonly used regional and global weather datasets in the economics literature (e.g. Dell et al., 2009, 2012; Jones & Olken, 2010; Nunn & Qian 2014), and for studies on Africa specifically (Arezki & Brückner, 2012; Burke, Gong, & Jones, 2015; Papaioannou & DeHaas, 2017). Appendix 1 gives more details on how this weather dataset is constructed and why it was chosen for this study.

The rainfall data is used to calculate a Standardized Precipitation Index (SPI) for each grid cell in the data. As outlined by Dinkelman (2017), according to the climatology literature, the SPI is an appropriate variable to use to indicate drought conditions. It is computed by first fitting a gamma distribution to the rainfall data to correct for the fact that rainfall is not normally distributed. Then, normalized annual averages for each gridcell are converted to z-scores, which indicate the number of standard deviations between annual rainfall in each grid cell, and the grid cell's long-run mean. This ensures that droughts are defined based on local norms, which is important given the wide diversity in climates in our dataset. Note that while we believe that fitting the raw rainfall data to a gamma distribution is methodologically important, it results in only a small change in the actual z-scores. The transformed and untransformed annual z-scores are both positively correlated with a coefficient near perfect at 0.98. Fig. 2 shows

[9] For further details of how this variable is computed refer to the Wealth Index construction page of the DHS website http://www.dhsprogram.com/topics/wealth-index/Wealth-Index-Construction.cfm.

[10] These are decisions regarding: food to be cooked, visits to family/friends, the respondent's own health, daily household purchases, and large household purchases.

[11] The DHS collects GPS coordinates of enumeration clusters for most recent surveys. While the GPS readings are accurate to <15 m, they randomly displace these coordinates in the publicly available data to ensure confidentiality of respondents. In urban clusters, this displacement is between 0 and 2 km, and in rural clusters it is between 0 and 5 km for 99% of clusters, and 0–10 km for 1% of clusters. Given that the resolution of our weather data is approximately 55 $\times$ 55 km, it is unlikely that this displacement would cause a cluster to fall into a different gridcell. In the few cases where this will happen, a cluster will be displaced no further than the adjacent gridcell, resulting in a minimal impact on observed weather.

Table 2
Descriptive statistics.

	Mean	Standard deviation	Minimum	Median	Maximum
Wealth index score	−0.440	0.584	−2.338	−0.557	6.282
Height (cm)	157.295	6.863	45.7	157.7	170.4
Education (years)	3.597	3.999	0	2	20
Husband has sole say in any household decisions	0.585	0.493	0	1.0	1
Has at least one low birth-weight child	0.140	0.347	0	0.0	1
Birth year	1978	10	1953	1980	1998
Annual average temperature (C)	23.910	4.352	4.783	24.925	31.625
Long run average annual precipitation (mm)	1123.896	590.214	93.161	997.159	3423.152
Standard Precipitation Index	−0.166	0.990	−4.327	−0.168	4.589
Fraction of early childhood in less severe drought (SPI < −1)	0.202	0.213	0	0.2	1
Fraction of early childhood in drought (SPI < −1.5)	0.093	0.145	0	0.0	1
Fraction of early childhood in more severe drought (SPI < −2)	0.038	0.089	0	0.0	1
Drought: 1.5 SD negative shock in year of birth	0.086	0.280	0	0	1
Abundance: 1.5 SD positive shock in year of birth	0.036	0.187	0	0	1
Extreme drought: 2 SD negative shock in year of birth	0.045	0.207	0	0	1
Large abundance: 2 SD positive shock in year of birth	0.016	0.127	0	0	1

Notes: Table shows descriptive statistics from the DHS surveys as well as the SPI data from Matsuura and Willmott (*op cit*). Sample based on 76,914 rural respondents who have not migrated from their birth place.

histograms of the two overlaid. It shows that the transformed z-scores are more symmetric around zero, with density shifting from just left of zero to just right of zero.

Following McKee, Doesken, and Kleist (1993), and in line with the threshold used by Dinkelman (2017), we then define a location-specific drought event as a year in which the SPI was 1.5 or more standard deviations below the long-run mean in a given grid cell (McKee et al. (1993) define periods when rainfall is at least 1.5 standard deviations below average as a severe or extreme drought event).[12] Similar to Dinkelman (2017), our main indicator of early-life drought is then the percentage of years, from the calendar year of birth (t) to the end of the fourth calendar year after birth (t + 4) where the local SPI is less than −1.5.[13] As robustness checks, we also modify this in several different ways: an indicator of drought only in the birth-year, t (Tables 5 And 6); a semi-parametric modelling of rainfall (Table A2); log deviation in rainfall in the year of birth, following Maccini and Yang (*op cit*) (Table A3); cumulative drought percentage ranging from year t to t + 3 (Table A5); and a semi-parametric specification where we group SPI into buckets and calculate the share of months that each bucket was experienced in a respondent's early-life period (Table A6). In our main tables we also test different thresholds for SPI (less than −1, and less than −2).

As Table 2 outlines, the long-run average of annual rainfall in the grid cells we analyze is 1105 mm, and the average annual temperature is approximately 24 degrees Celsius. There is significant variation in climates, with average annual rainfall levels ranging from 93 mm/year in Kidal, in the desert region of northern Mali, to 3423 mm/year in the Pujehun District of southern Sierra Leone. The average annual SPI value is −0.166 indicating that drier than average years are little more common than wetter years in our sample. Approximately 8.6 percent of respondents were born during a drought year (SPI of −1.5 or less), the average respondent in our sample spent 9.3 percent of their first five years of life (the period we define as early childhood) in drought conditions, while 4.5 percent were born in a period of abundant rainfall (SPI ≥ 1.5). The relative frequencies of droughts and abundant rain have been evolving over the period covered by our analysis with droughts becoming increasingly prevalent over time. One percent of women born in the 1950s experienced droughts in their year of birth, while 14 percent of women born in the 1990s were born in a drought year.

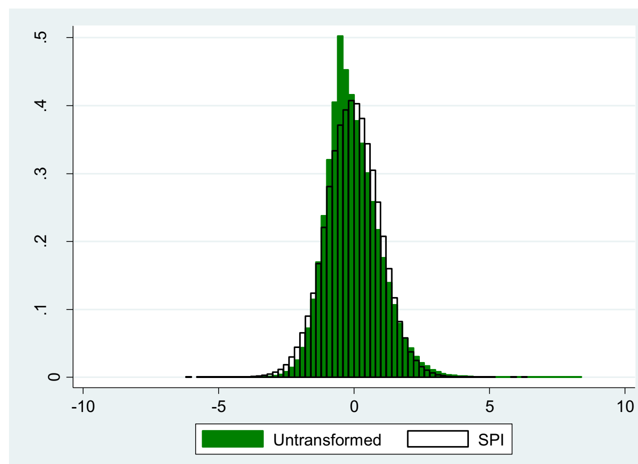

Fig. 2. Transformed versus untransformed z-scores of annual precipitation data
Notes: Figure shows the histogram of z-scores from the raw annual weather data (green) and the transformed, standardized precipitation index (white). Gridcells which are included are those where a DHS enumeration area falls into them in any of the surveys included in this study. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Methodology

To isolate the impact of drought conditions in early life on adult household wealth, we exploit the quasi-natural experiment created by fluctuations in weather patterns. We focus on local deviations in rainfall levels from their long-run, local means. Identification rests on the assumption that while long-run weather patterns may be endogenous to outcomes such as wealth, large deviations from long-run means will be unexpected and therefore exogenous. Formally, we estimate the following equation:

$$Y_{ijt} = \alpha + Drought_{ijt} + Year_t \times Country_c + \delta_{GC} + \vartheta_M + AvgMonthlyTemp_{jt} + \varepsilon_{ijt} \quad (1)$$

[12] The long run mean is based on the full time period of the Matsuura and Willmott data, 1900–2013. There may be some concern that local climates have changed over that time period, and thus our definition of droughts would be sensitive to our time period choice. To test the sensitivity of the weather data to the long run mean time period, we calculate rainfall z-scores based on 2 additional time periods, 1930–2013, and 1950–2013. The z-scores based on the full time period correlate with these at 98.0% and 97.1%, respectively, thus confirming that the definition of drought is not sensitive to changes in the long run time period.

[13] Note that because our drought indicator is calculated based on the calendar year; this measure will capture part of the in-utero period for many of the respondents.

where $Y_{i,j,t}$ represents the various long-term outcomes considered (adult wealth, education, height, empowerment and intergenerational impacts) for respondent i, born in grid cell j, and year t. As noted previously, a drought is defined as a SPI value of less than -1.5 in gridcell j in a given year. $Drought_{ijt}$, our main variable of interest, measures the share of years in which the respondent was exposed to drought during her early childhood, as described in section 2.2. $Year_t \times Country_c$ are country-by-birth-year fixed effects, and δ_{GC} and ϑ_M represent grid cell and birth-month fixed effects, respectively. $AvgMonthlyTemp_{jt}$ is the grid cell average monthly temperature in each of the years of early childhood (to control for correlation between temperature and rainfall in each of these years). Finally, ε_{ijt} is a random error term. For our main results, we cluster our standard errors at the country-year level. However, in Appendix 2, we also show that our main results are robust to alternative levels of clustering (Table A1). In addition, Appendix 2, also shows results for alternative specifications of rainfall levels (Tables A2 and A3), and an alternative definition of early childhood (Table A5).

Our main outcome of interest is the long-term impacts of rainfall in infancy on adult wealth. To examine intermediate mechanisms, we also estimate the relationship between early-life droughts and educational attainment (completed years of formal schooling) and adult height. To test whether the long-term impacts of rainfall also spill-over into the behavioral domain, we examine its long-term impacts on women's empowerment within their households. Finally, to test whether there is an intergenerational impact of early-life drought, we examine the birth weight of the respondents' children. We define a dummy variable that is equal to one if a respondent has at least one low-birth-weight child. Thus, the outcome variable in Eq. (1) can represent, in various models, adult wealth (as measured by the DHS wealth index score), completed years of schooling, adult height (in centimeters), female empowerment (as proxied by the respondent's self-stated role in household decision making), and a low birth weight dummy.

4. Results

Table 3 shows results from estimating Eq. (1) for the wealth index for our urban sample and rural sample separately. Results show that there is a long term, negative impact of early-life exposure to drought on women's wealth in rural areas. However, we find no long-term impact of drought on women born and raised in urban areas; this suggests that the channel through which early-life drought affects adult women is likely, at least in part, due to a negative impact on agricultural output, on which households in rural areas are more heavily-reliant. Our main drought threshold is an SPI less than -1.5 (columns 1–2), however, we also test alternative thresholds to see how women are affected by both less (columns 3–4) and more severe (columns 5–6) drought conditions. We find that the impact increases in magnitude and statistical significance as the depth of the drought increases. These results are consistent with the findings of Maccini and Yang (2009) and Abiona (2017), who also find evidence of long-term impacts of early-life weather conditions, and, thus, shows that their results for Indonesia and Malawi, respectively, are generalizable to a wider context. In addition to testing the impacts of cumulative drought exposure in early childhood, we also control for drought shocks occurring prior to birth (which will partially include the time in-utero), and find no effect of droughts occurring during this time period. As we find evidence of a long-term impact of drought only for rural households, and only for the period of early childhood after the year of birth, for the remainder of the analysis we focus on women in these households, and only on drought exposure during early childhood. Table A1 in Appendix 1 shows that our main results are robust to different levels of clustering.

Table 4 displays results from estimating Eq. (1) where the dependent variables are our measures of human capital—education (columns 1,3 and 5) and height (columns 2, 4 and 6). These outcomes may also represent estimates of a medium-term impact of drought, since for most women these outcomes are determined before they reach adulthood. Results in columns 1, 3, and 5 illustrate that experiencing a drought at any of the drought thresholds has a negative impact on education levels, with the magnitude of the effect increasing as the drought measure becomes more severe. However, we find that it takes a severe drought (SPI < -2) to leave a statistically significant impact on height. Given that stunting requires significant nutritional deprivation over an extended period of time, it is perhaps not surprising that the height indicator is less sensitive to milder droughts. Both education and height

Table 3
The long-term impacts of drought on wealth.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPI < −1.5		SPI < −1		SPI<−2	
	Rural	Urban	Rural	Urban	Rural	Urban
Cumulative exposure to drought (SPI < −1.5)	−0.035**	0.031				
	(0.018)	(0.048)				
Drought shock in t − 1 (SPI < −1.5)	0.008	−0.002				
	(0.008)	(0.021)				
Cumulative exposure to mild drought (SPI < −1)			−0.017	−0.016		
			(0.014)	(0.036)		
Drought shock in t − 1 (SPI < −1)			0.004	0.001		
			(0.006)	(0.016)		
Cumulative exposure to exceptional drought (SPI < −2)					−0.065**	−0.004
					(0.028)	(0.071)
Drought shock in t − 1 (SPI < −2)					0.015	0.005
					(0.012)	(0.026)
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects					
Number of observations	76,902	29,386	76,902	29,386	76,902	29,386
R2	0.331	0.460	0.331	0.460	0.331	0.460

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable is the household wealth index provided by the DHS. Drought is calculated using the standardized precipitation index (SPI) and is defined over the period starting at the calendar year of birth, up until 4 years after birth. Columns 1 and 2 use a threshold of SPI < −1.5; columns 3 and 4 use a threshold of SPI < −1 and columns 5 and 6 use a threshold of SPI < −2. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

Table 4
The long-term impact of drought on human capital – Rural households.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPI < −1.5		SPI < −1		SPI < −2	
	Education	Height	Education	Height	Education	Height
Cumulative exposure to drought (SPI < −1.5)	−0.449***	−0.121				
	(0.156)	(0.300)				
Cumulative exposure to mild drought (SPI < −1)			−0.437***	−0.318		
			(0.116)	(0.222)		
Cumulative exposure to exceptional drought (SPI < −2)					−0.608***	−1.022**
					(0.212)	(0.465)
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects					
Number of observations	76,857	52,733	76,857	52,733	76,857	52,733
R2	0.556	0.174	0.556	0.174	0.556	0.174

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable in columns 1, 3 and 5 is total years of education of the female respondent, and in columns 2, 4 and 6 is height (cm) of the female respondent. Drought is calculated using the standardized precipitation index (SPI) and is defined over the period starting at the calendar year of birth, up until 4 years after birth. Columns 1 and 2 use a threshold of SPI < −1.5; columns 3 and 4 use a threshold of SPI < −1 and columns 5 and 6 use a threshold of SPI < −2. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

are associated with increased long-term wealth and thus these variables may represent potential transmission channels from early-life drought conditions to adult wealth. Maccini and Yang (2009) also provide suggestive evidence that accumulation of human capital represents a possible pathway through which early-life rainfall shocks impact wealth.

The negative impacts of drought on wealth, educational attainment, and height are confirmed by alternative specifications of the drought measure. We test the impact of a single drought shock in the respondent's year of birth on her long-term wealth, educational attainment, and height. In this specification, we also test whether analogous periods of abundant rainfall (SPI > 1, 1.5, and 2, respectively) have corresponding positive impacts. Table 5 confirms our previous findings that negative rainfall shocks have long-term negative impacts on wealth in rural households, and it also shows that periods of abundant rainfall have a positive long-term impact. A likely reason is that a positive rainfall shock would have a positive impact on agricultural output and, thus, household resources in rural areas. Similar to our previous findings, we do not detect any impact of rainfall shocks, positive or negative, on long-term wealth in urban households. Table 5 shows a significant impact when SPI < −1.5, however, when we restrict SPI < −2, the point estimates lose significance (while retaining the correct sign); this is possibly due to a lack of statistical power as far fewer respondents are exposed to such shocks – while about 8.6% of our sample experience a SPI < −1.5 shock in their birth year, only 3.6% experience a more extreme shock. Table 6 shows that experiencing a negative rainfall shock in the year of birth has no significant long-term impacts on education and height, although the point estimates are all negative. That these results which use single-year estimates are much noisier than the 5-year drought period tested in Tables 3 And 4 suggests that it may take cumulative drought periods for an impact to transpire.[14] This may be evidence of a household's ability to adapt to a short-term shock, perhaps through consumption smoothing, but an inability to adapt to longer term shocks.

In Table 7 we show results for the impact of early-life shocks on women's empowerment (columns 1, 3 and 5) and second-generation impacts (columns 2, 4 and 6). We find that women who experienced droughts of at least −1.5 SPI had an increased probability of being in a household where her husband/partner alone decides on household issues. In addition to this, we find evidence that women who experienced an extreme drought (SPI < −2) in their childhood are more likely to give birth to low birth weight children.

It is important to note that there are several ways of specifying the drought variable and thus, to test the robustness of our results, we try several additional specifications. These results are presented and discussed in Appendix 2. These results generally confirm our main findings, though some inconsistencies are highlighted and discussed. Finally, to ensure that the relationship that we uncover between rainfall shocks in a child's earliest years and their adult wealth is not merely a spurious correlation, we test for an impact in years in which there should not be a significant relationship between shocks and adult wealth. Specifically, we test for an impact of rainfall shocks ten to twenty years before the respondent was born, and for the same period after her birth. As Figs. 3 and 4 illustrate, none of the coefficients on these shock variables are significant. This further verifies that periods of drought around the time of birth can have significant long-term consequences.

5. Discussion and conclusions

Our results provide evidence that unanticipated drought conditions experienced in a child's earliest years can have significant, long-term implications. We find that the socio-economic status of women in rural households in sub-Saharan Africa is affected by the weather conditions that they experienced decades earlier. Furthermore, drought exposure during early life is significantly associated with lower levels of education and, in the case of extreme drought, reduced height. This impact of drought on height is particularly important in the context of sub-Saharan Africa where over 35 percent of children under five are stunted (i.e., height for age that is two or more standard deviations below the reference mean). NCD Risk Factor Collaboration (2016) discusses global trends in average height and notes that, over the past century, the average height of a woman in Africa has increased by only 2 cm. Thus, experiencing severe drought in infancy would negate much of this gain. The likely channel between drought and adult outcomes is that droughts alter household income and nutritional intake, with important consequences for physical and cognitive development. Our results concur with those of, for example, Alderman et al. (2006), Maccini and Yang (2009), Carrillo et al. (2015), Abiona (2017), and Dinkelman (2017) who find significant

[14] Hoddinott and Kinsey (2001) find that children's growth is affected by drought if the drought occurs when the child is between 12 and 24 months, but they do not test the impact on younger children.

Table 5
The long-term impacts of a rainfall in birth year on wealth score.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPI: 1.5		SPI: 1		SPI: 2	
	Rural	Urban	Rural	Urban	Rural	Urban
Positive rainfall shock (SPI > 1.5)	0.024**	−0.017				
	(0.010)	(0.027)				
Negative rainfall shock (SPI < −1.5)	−0.018**	0.023				
	(0.008)	(0.023)				
Positive rainfall shock (SPI > 1)			0.016**	−0.003		
			(0.008)	(0.022)		
Negative rainfall shock (SPI < −1)			−0.005	−0.014		
			(0.006)	(0.016)		
Positive rainfall shock (SPI > 2)					0.022	−0.042
					(0.014)	(0.047)
Negative rainfall shock (SPI > 2)					−0.005	−0.010
					(0.013)	(0.033)
Controls	Temperature t; gridcell fixed effects; country X year fixed effects; birth-month fixed effects					
Number of observations	76,902	29,386	76,902	29,386	76,902	29,386
R2	0.331	0.460	0.331	0.460	0.331	0.460

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable is the household wealth index provided by the DHS. Drought and abundant rainfall is calculated using the standardized precipitation index (SPI) and is defined over the calendar year of birth. Columns 1 and 2 use a threshold of SPI < −1.5 for drought and SPI > 1.5 for abundance; columns 2 and 3 use a threshold of SPI < −1 for drought and SPI > 1 for abundance, and columns 5 and 6 use a threshold of SPI < −2 for drought and SPI > 2 for abundance. Standard errors are clustered at the country-year level, and are presented in parentheses.
***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

Table 6
The long-term impacts of a rainfall in birth year on education and height – rural households.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPI < −1.5		SPI < −1		SPI < −2	
	Education	Height	Education	Height	Education	Height
Positive rainfall shock (SPI > 1.5)	−0.038	−0.085				
	(0.058)	(0.176)				
Negative rainfall shock (SPI < −1.5)	−0.037	−0.088				
	(0.081)	(0.144)				
Positive rainfall shock (SPI > 1)			0.020	−0.044		
			(0.049)	(0.134)		
Negative rainfall shock (SPI < −1)			−0.006	−0.063		
			(0.050)	(0.111)		
Positive rainfall shock (SPI > 2)					−0.100	−0.128
					(0.091)	(0.278)
Negative rainfall shock (SPI > 2)					−0.033	−0.055
					(0.125)	(0.254)
Controls	Temperature t; gridcell fixed effects; country X year fixed effects; birth-month fixed effects					
Number of observations	76,857	52,733	76,857	52,733	76,857	52,733
R2	0.555	0.174	0.555	0.174	0.555	0.174

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable in columns 1,3 and 5 is total years of education of the female respondent, and in columns 2,4 and 6 is height (cm) of the female respondent. Drought and abundant rainfall are calculated using the standardized precipitation index (SPI) and are defined over the calendar year of birth. Columns 1 and 2 use a threshold of SPI < −1.5 for drought and SPI > 1.5 for abundance; columns 3 and 4 use a threshold of SPI < −1 for drought and SPI > 1 for abundance, and columns 5 and 6 use a threshold of SPI < −2 for drought and SPI > 2 for abundance. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

long-term impacts of weather conditions experienced in a child's earliest years on its later-life outcomes. However, while these early studies were confined to individual countries, the wide geographical and temporal scope of our analysis confirms that these effects hold when assessed on a broader scale.

While previous analyses of the long-term impacts of environmental shocks have tended to focus on their effects on socio-economic status and measures of human capital, we assess the impacts across a broad range of outcomes including wealth, education, height, and female empowerment, and find evidence of the long-term impacts of drought across this broad spectrum. Furthermore, our results show that not only are women haunted by the long-term impacts of drought that they experienced in their infancy, but that their children also bear the hallmarks of these episodes of severe rainfall deficits. We find that the likelihood that a woman in our analysis will give birth to a low birth weight child is increasing in the proportion of her early childhood that was spent in drought conditions. This result expands on the findings of Comfort (2016) who finds a long-term link between rainfall shocks and maternal mortality and health. Our findings also build upon those of Grace et al. (2015) who document a significant short-term impact of weather on birth weight. The consequences of being born with a low birth weight may be significant – research by Behrman and Rosenzweig (2004) shows that increased weight at birth is associated with increased education, height, and positive labor market outcomes. Research by Victora et al. (2008) shows a

Table 7
The long-term impacts of drought on agency and second-generation impacts.

	(1)	(2)	(3)	(4)	(5)	(6)
	SPI < −1.5		SPI < −1		SPI < −2	
	Lacks agency	LBW child	Lacks agency	LBW child	Lacks agency	LBW child
Cumulative exposure to drought (SPI < −1.5)	0.041***	0.097				
	(0.019)	(0.038)				
Cumulative exposure to mild drought (SPI < −1)			0.035***	0.026		
			(0.014)	(0.023)		
Cumulative exposure to exceptional drought (SPI < −2)					0.013***	0.026**
					(0.030)	(0.053)
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects					
Number of observations	60,440	14,731	60,440	14,731	60,440	14,731
R2	0.304	0.147	0.304	0.146	0.304	0.146

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable in columns 1, 3 and 5is an indicator equal to 1 if the female respondent's husband/partner has the sole say in any household decisions, and 0 otherwise, and in columns 2, 4 and 6 an indicator equal to 1 if any of the female respondent's children were born with below normal birthweight (<2.5 kg). Drought is calculated using the standardized precipitation index (SPI) and is defined over the period starting at the calendar year of birth, up until 4 years after birth. Columns 1 and 2 use a threshold of SPI < −1.5; columns 3 and 4 use a threshold of SPI < −1 and columns 5 and 6 use a threshold of SPI < −2. Standard errors are clustered at the country-year level, and are presented in parentheses.
***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

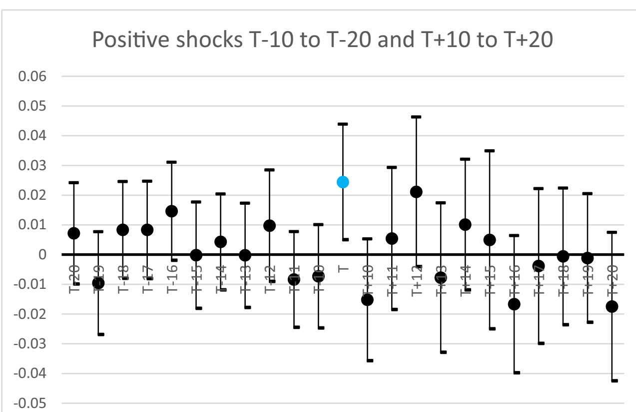

Fig. 3. Falsification test – positive shocks *Notes:* Figure shows plotted coefficients and 95% confidence intervals from estimating a modified version of Eq. (1), 21 times. Positive shocks are denoted as years in which rainfall is at least 1.5 SPI. Each coefficient is estimated from a separate regression. T denotes the true time period, whereas T-X represents the shift, in years, of the weather variable (i.e. T-20 shows the 20 year lagged weather data for a particular household).

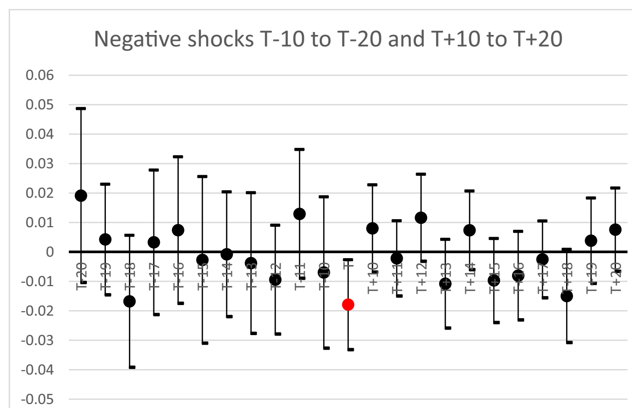

Fig. 4. Falsification test – negative shocks *Notes:* Figure shows plotted coefficients and 95% confidence intervals from estimating a modified version of Eq. (1), 21 times. Negative shocks are denoted as years in which rainfall is less than −1.5 SPI. Each coefficient is estimated from a separate regression. T denotes the true time period, whereas T-X represents the shift, in years, of the weather variable (i.e. T-20 shows the 20 year lagged weather data for a particular household).

positive relationship between a woman's birth weight and that of her offspring, which suggests that the impact of drought could cascade through multiple generations.

The intergenerational transmission of rainfall shocks may reflect a biological link between mothers and their children, it may be reflective of the impact of childhood rainfall on household wealth, or it may reflect other dynamics within in the household. For example, it has been shown that where women have greater responsibility for household finances, a greater proportion of household income is spent on children and on food (see, for example, Hoddinott & Haddad, 1995; Duflo, 2003; Bobonis, 2009). Indeed, there is a well-documented link between female empowerment and economic development (refer to Duflo, 2012 for a detailed overview of this literature). We find that early-life rainfall shocks impact women's empowerment later in life which may partly explain the intergenerational shock transmission. By shedding new light on the intergenerational transmission of environmental shocks, our research suggests that previous estimates of the costs of environmental shocks may have been significantly underestimated.

A possible source of bias in our estimates is the impact of drought on infant-mortality rates. The population whose adult outcomes we observe (along with those of their children) may represent a subsample of the population who are physically stronger and were thus able to survive periods of drought. Evidence that weather conditions can impact mortality rates in the United States is provided by Deschênes and Greenstone (2011). If drought does have a direct impact on infant mortality in our sample, its long-term impacts on those individuals who did not survive the drought would be expected to be larger. Thus, our results likely provide a lower-bound estimate of the long-term impacts of rainfall in infancy.

What then do our results mean for development policy? Our research serves to highlight the extreme vulnerabilities of one of the poorest populations in the world to the types of environmental shocks that are forecast to become ever more frequent as a result of climate change. This underscores the need to increase the scale up and roll out of safety net programs,[15] triggered without delay when disasters hit. Delaying, or failing to respond to drought and famine may have, in addition to the immediate costs resulting from

[15] Research for the US, by Hoynes, Schanzenbach and Almond (2016), has shown the positive impact of childhood safety nets on socioeconomic outcomes for women.

mortality and morbidity, long-term impacts that remain invisible for decades but cost countries in terms of economic growth and act as a barrier to economic development. Adding to this urgency, McDermott, Barry, and Tol (2013) shows that low-income countries are more likely to suffer long-term negative impacts of natural disasters in terms of reduced economic growth. As Strömberg (2007) notes, economic development provides resilience to shocks; however, this will not be achieved if the destinies of the most vulnerable people on the planet are left to the vagaries of rainfall.

Nutritional interventions may also help protect vulnerable households when environmental shocks strike. To achieve the greatest possible cost-effectiveness, these interventions should be targeted where a significant body of evidence suggests that they are most effective – during the first "1000 days of life". Coupling these interventions with educational programs may further boost their effectiveness. Beyond the role of social safety nets, weather-indexed insurance may protect rural families from the long-term impacts of drought. Hazell and Hess (2010) note that such insurance could serve to boost investment in new agricultural technologies that drive farm productivity, and would also increase the long-term resilience of agricultural households to negative rainfall shocks.

Another means of buffering rural populations against droughts is water storage infrastructure, particularly for irrigation. If water is stored during times of plenty, it can be released during times of drought to ensure sufficient levels for agricultural production, as well as for health and hygiene. In Appendix 3, we test whether being located within the command area of upstream irrigation facilities buffers individuals against the same long-run impact of negative rainfall shocks studied in this article. While we do find that being born within the command area of irrigation facilities boosts long-run wealth, we do not find evidence that it is able to buffer families against these rainfall shocks. This may be due to poor management of the facilities themselves—i.e. they may be able to provide irrigation benefits during normal times, but do not have the storage capacity, or are not managed well enough, withstand severe droughts. This subject warrants more in-depth study.

It is worth emphasizing the importance of our findings. Across an array of countries, and over a long period, we find that the environmental conditions experienced in a female child's earliest years have significant long-term impacts, which may in turn be transmitted to her children. If these children end up less wealthy as adults, the effects of rainfall shocks experienced by rural households in sub-Saharan Africa may persist across many generations.

Acknowledgements

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Appendix 1. Weather data

A limited number of datasets exist which offer annual rainfall data for large regions of sub-Saharan Africa for the second half of the 20th century (see Auffhammer, Hsiang, Schlenker, & Sobel, 2013 for a review). For this study, we selected the University of Delaware's Global Land Temperature and Precipitation Data (Matsuura & Willmott, 2012a, 2012b), henceforth referred to as the UDEL dataset. This dataset was selected for several reasons: it is available at a spatially granular level (the 0.5 degree gridcell, approximately 55 km^2 at the equator), for the entirety of the 20th century, allowing us to calculate long term averages; it is based on historical weather observations rather than weather models, thus increasing its accuracy; and uses a highly dense network of weather stations during the time period of our analysis.

The global dataset is constructed from data from five different sources, three of which cover Africa: Global Historical Climatology Network (GHCN), Sharon Nicholson's archive of African precipitation data, and the station climatologies from Legates and Willmott's archive.[16] GHCN includes data from at least 1308 weather stations in Africa (1239 of which are from the African Historical Precipitation Data, and 69 are from Roucou's data set for Africa[17]). Sharon Nicholson's archive broadly covers southern Africa with 1338 stations over the time period 1840–1996 (from 1950 to 1996, this number varies from 791 to 1263). Finally, Legates and Willmott do not specify the number of stations in Africa, but include over 24,000 spatially independent weather station records on land, and over 22,000 oceanic station records.

Fig. A1 shows the final distribution of stations every 10 years from 1950 to 1990. Note that the entire Sub-Saharan Africa region is very well covered over the time period of this study. In 1990, coverage in some Central African countries become patchy. This appears to be due to several stations in Democratic Republic of Congo leaving the dataset in 1988. This is not too concerning, as less than one percent of the entire sample of non-migrant respondents appear in our dataset from DRC, post-1988. While the UDEL data does not release aggregate data station counts specific for Africa, they do state that observations peaks in 1968, where globally there were 13,700 unique station observations. The number of stations overtime are shown in Fig. A2. Thus, the number of weather stations was deemed suitable for this study, and may be more suitable for the time period examined here than a study over a more recent time period.

Several weather dataset options exist for researchers conducting global studies. The three most common in the economics literature are 1) the UDEL dataset (Matsuura and Willmott, *op cit*), 2) the Climatic Research Unit (CRU) at the University of East Anglia (Mitchell and Jones, 2005), and 3) NCEP/National Center for Atmospheric Research (NCAR) (Kistler et al., 2001). We evaluated all three of these datasets and determined that the UDEL dataset was the most appropriate for this paper's context. Both UDEL and CRU use observational data from historic weather stations, and use spatial interpolation between these stations to create a global grid, while NCEP is reanalysis data, based on physical weather models. Each of these two types of data have benefits and drawbacks, and are reviewed by Auffhammer et al. (*op cit*).

While the UDEL and CRU data are quite similar in their construction and correlate very highly (0.917 with temperature and 0.698 with rainfall according to Auffhammer et al. (*op cit*)), NCEP/NCAR uses a much different methodology and only correlates far less with UDEL (0.742 for temperature and 0.269 with rainfall).

The NCEP/NCAR reanalysis data was rejected for this study for two reasons. The first, practical reason is that NCEP/NCAR data is only available beginning in 1948. While the earliest birth in our dataset is in 1953, we require a long panel prior to this year in

[16] See http://climate.geog.udel.edu/~climate/html_pages/Tropics_files/README.tropic_precip_ts.html.

[17] See https://www.ncdc.noaa.gov/ghcnm/v2.php.

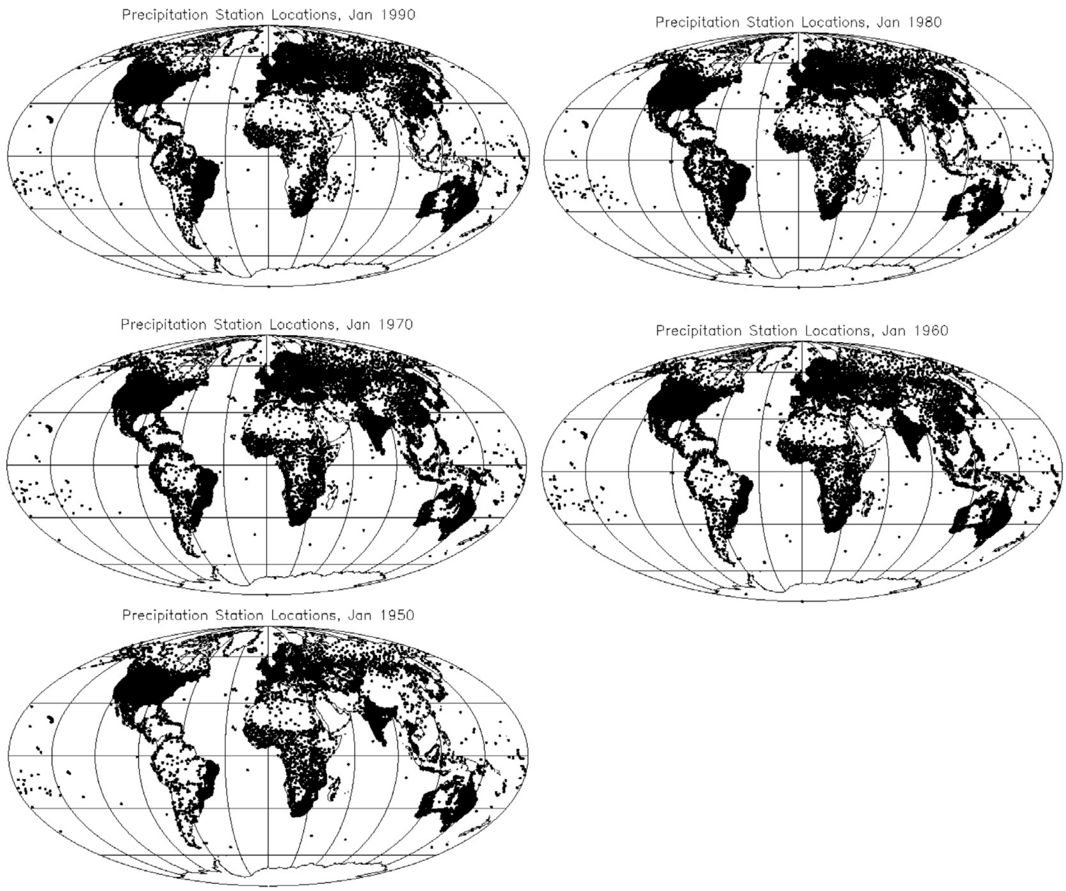

Fig. A1. UDEL dataset distribution of precipitation stations (1950–1990) Figure shows the distribution of weather stations used to construct the UDEL dataset on global precipitation from 1950 to 1990, at 10-year intervals. *Source:* http://climate.geog.udel.edu/~climate/html_pages/Global2017/GlobalTsP2017Loc.html.

Table A1
The long-term impacts of drought on wealth, different levels of clustering.

Level of Clustering:	(1) Province	(2) Province-year	(3) Province-survey year	(4) Grid cell
Cumulative exposure to drought (SPI < −1.5)	−0.032*	−0.032**	−0.032*	−0.032*
	(0.016)	(0.016)	(0.017)	(0.016)
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects			
Number of observations	76,902	76,902	76,902	76,902
R2	0.331	0.331	0.331	0.331
Number of clusters	292	8,583	407	1,572

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS) for the rural population sample. Each column displays estimates from a separate regression. The dependent variable is the household wealth of the female respondent. Drought is calculated using the standardized precipitation index (SPI) and is defined over the period starting at the calendar year of birth, up until 4 years after birth, with SPI < −1.5 used as the cutoff to define drought. From columns 1–4, standard errors (in parentheses) are clustered at province, province-year, province-survey year, and weather gridcell, respectively. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

order to determine the long run mean and standard deviation of rainfall in order to calculate our rainfall shocks. The second reason deals with how the data is constructed. Reanalysis data is useful when observations are few and far between. In these situations, spatial interpolation will fail to accurately capture weather in regions far away from weather station data. However, when there is a large amount of weather stations available, as is the case with the UDEL data, the bias in real analysis data is likely to exceed that from spatial interpolation. Even in locations where weather station data is available, reanalysis datasets will still rely on the output of the global climate model (Auffhammer et al. *op cit*), which are merely estimates. Thus, a spatially interpolated weather dataset will always be preferable to a reanalysis dataset when there is a sufficient concentration of weather stations.

Appendix 2. Robustness checks to alternative ways of measuring rainfall

In Appendix 2 we display results from alternative specifications and robustness checks.

As a first robustness check, we test the sensitivity of our analysis to different levels of clustering. Table A1 displays results from

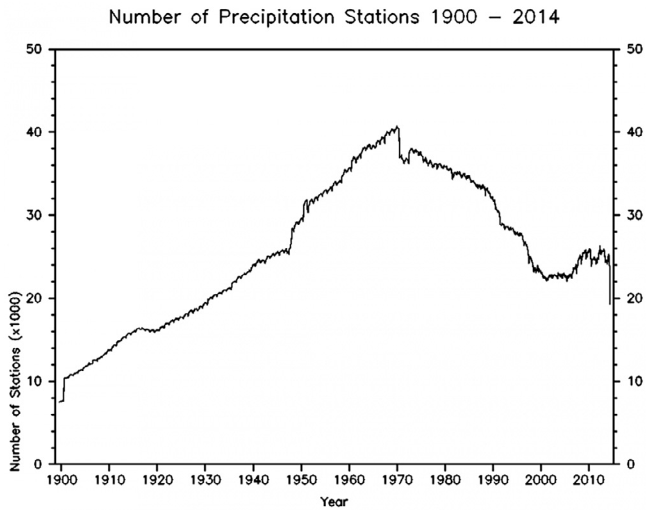

Fig. A2. UDEL data precipitation stations over time, globally *Source:* Matsuura and National Center for Atmospheric Research Staff (2017).

Table A2
A semi-parametric modelling of rainfall – the long-term impacts of rainfall on wealth.

	Dependent variable: Wealth
Quartiles of rainfall:	
Min-P25:	−0.0372**
<665.7 mm	(0.0169)
P25-Median:	−0.0253*
665.7–970.9 mm	(0.0129)
Median-P75:	−0.0158*
970.9–1391.5 mm	(0.0090)
P75-Max:	*Reference category*
1391.5 mm+	
Controls	Temperature t; gridcell fixed effects; country X year fixed effects; birth-month fixed effects
Number of observations	76,914
R2	0.331

Notes: Table shows results from estimating a modified version of Eq. (1) via ordinary least squares (OLS) for the rural population sample. The dependent variable is the household wealth of the female respondent. The rainfall measures are broken into quartiles, where the lowest quartile (0–665.7 mm) is the omitted category. Standard errors are clustered at the country-year level and are presented in parentheses. Additional controls included in the model are fixed effects for grid cell, respondent's month of birth, and country of birth interacted with year of birth. ***, **, * denote significance at the 1%, 5% and 10% levels respectively

estimating Eq. (1) where the dependent variable is the household wealth of the female respondent, and, in each column, standard errors are clustered at different levels: province, province-year, province-survey year, and weather gridcell, respectively. The estimates show that the results are robust to various levels of clustering, and remain significant for all levels. Overall, the standard error on the drought coefficient is very insensitive to the level of clustering.

In the main part of our analysis we test the effects of rainfall shocks using two alternative measures: firstly, by measuring cumulative drought exposure and, secondly, by using drought and rainfall abundance dummies in birth year. Here we show that the impact of rainfall on wealth is consistent when using two additional methods of modelling rainfall.

In the first instance, we test the relationship between rainfall and wealth using the absolute quantity of rainfall, divided into a number of bins. Our results, displayed in Table A2 below, show that, relative to the highest rainfall bin (the omitted category),

Table A3
Effect of rainfall shock in the year of birth on wealth and human capital, using an alternative measure of the rainfall shock.

	(1)	(2)	(3)
	Wealth	Education	Height
Rainfall shock in year of birth ($log\_rainfall_t$ minus log_avg_rainfall)	0.0332**	0.0451	−0.308
	(0.0142)	(0.116)	(0.268)
Controls	Temperature t; gridcell fixed effects; country X year fixed effects; birth-month fixed effects		
Number of observations	76,914	76,869	52,767
R2	0.331	0.555	0.174

Notes: Table shows results from estimating a modified version of Eq. (1) via ordinary least squares (OLS) for the rural population sample. The dependent variable is the household wealth of the female respondent. Rainfall shock is defined as the log deviation in annual rainfall in a grid cell in year t from the long-run mean rainfall in that grid cell. Standard errors are clustered at the country-year level and are presented in parentheses. Additional controls included in the model are fixed effects for grid cell, respondent's month of birth, and country of birth interacted with year of birth. ***, **, * denote significance at the 1%, 5% and 10% levels respectively

lower amounts of rainfall in birth year are associated with lower levels of long-term wealth.

Secondly, we model rainfall following the specification used by Maccini and Yang (2009), which is the log deviation in rainfall in each grid cell. When we model rainfall in this way, the relationship between rainfall and wealth remains statistically significant. However, in this instance, the relationships between rainfall and education, and rainfall and height, do not; this is illustrated in Table A3.

As an additional robustness test, we split the data into two time periods—for women born pre-1980 and those born post-1980—and we test whether the results hold across both time periods. The results displayed in Table A4 below show that the impacts of drought are notably stronger in the period from 1980 onwards. For the women born before 1980, the results are not statistically significant. A possible explanation is that droughts were relatively less common over this earlier time period, and, therefore, these estimates may lack sufficient statistical power to detect an effect. Another inconsistency in the results should be noted here – when we split the sample for pre/post-1980 births, the results for height and female empowerment are not significant in either period. For both outcomes, the post-1980 results have the correct sign but large standard errors, thus we believe that a possible explanation for these insignificant results is that the reduced sample size for these regressions lack sufficient statistical power. The other relationships appear to be strong enough to survive the reduced sample size.

In the next robustness test, we present a slight modification of our main specification, and redefine the period of early childhood to a shorter, four-year time period (from year of birth, up to three years after birth), and test the impact of cumulative drought exposure over this time period. Table A5 below shows that our results are robust to this alternative definition of early childhood. Indeed, all results, presented in Tables 3 and 4 (our main specification) hold. One anomaly that appears here is that while both less severe ($SPI < -1$) and more severe ($SPI < -2$) droughts appear to have an impact on height, our standard drought threshold of -1.5 does not. However, closer inspection of the standard errors reveals that the coefficients on $SPI < -1$ and $SPI < -1.5$ are not statistically different, thus it is likely that a small impact is being picked up for $SPI < -1$ as these are more frequent. The much larger impact that we see on height for an $SPI < -2$ shock is more consistent with our main results (Table 4).

Finally, we test a semi-parametric specification, which measures the number of months, over the same early-life period as

Table A4
Results for women born before and after 1980.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Wealth		Education		Height		Lacks agency		LBW child	
	Pre-1980	Post-1980	Pre-1980	Post-1980	Pre-1980	Post-1980	Pre-1980	Post-1980	Pre-1980	Post-1980
Cumulative exposure to drought (SPI < −1.5)	−0.024	−0.051**	−0.027	−0.384**			−0.004	0.033	0.041	0.146**
	(0.031)	(0.025)	(0.198)	(0.182)			(0.031)	(0.024)	(0.066)	(0.057)
Cumulative exposure to exceptional drought (SPI < −2)					−0.739	−0.765				
					(0.916)	(0.618)				
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects									
Number of observations	36,575	40,213	36,559	40,184	25,130	27,427	33,037	27,240	7,126	7,294
R2	0.346	0.336	0.508	0.568	0.196	0.186	0.254	0.368	0.201	0.168

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable in columns 1 and 2 is wealth, in column 3 and 4 is education (in years), is column 5 and 6 is height (in cm), in columns 7 and 8 is an indicator equal to 1 if the female respondent's husband/partner has the sole say in any household decisions, and 0 otherwise, and in columns 9 and 10 is an indicator equal to 1 if any of the female respondent's children were born with below normal birthweight (<2.5 kg). The standard measure of drought, as in Tables 3, 4 and 7, is applied. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

Table A5
Effect of drought on wealth and human capital, using a shorter definition of childhood.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	SPI < −1.5			SPI < −1			SPI < −2		
	Wealth	Education	Height	Wealth	Education	Height	Wealth	Education	Height
Cumulative exposure to drought (SPI < −1.5)	−0.032**	−0.346**	−0.239						
	(0.016)	(0.137)	(0.272)						
Cumulative exposure to mild drought (SPI < −1)				−0.006	−0.294***	−0.402**			
				(0.012)	(0.100)	(0.191)			
Cumulative exposure to exceptional drought (SPI < −2)							−0.050**	−0.348*	−1.165***
							(0.024)	(0.188)	(0.419)
Controls	Temperature t:t + 3; gridcell fixed effects; country X year fixed effects; birth-month fixed effects								
Number of observations	76,902	76,857	52,733	76,902	76,857	52,733	76,902	76,857	52,733
R2	0.331	0.556	0.174	0.331	0.556	0.174	0.331	0.556	0.174

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variables are the household wealth index (columns 1, 4 and 7), the respondent's education, as measured by completed years of schooling (columns 2, 5 and 8), and the respondent's height in cm (columns 3, 6 and 9). Drought is calculated using the standardized precipitation index (SPI) and is defined over the period starting at the calendar year of birth, up until 3 years after birth. Columns 1 to 3 use a threshold of SPI < −1.5; columns 4 to 6 use a threshold of SPI < −1, and columns 7 to 9 use a threshold of SPI < −2. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

used in our main specification – year of birth and up to four years after birth, where the SPI fell into different bins of SPI severity. The SPI bins were formed in intervals of 0.5 from −2 to +2 SPI (i.e., $SPI < -2$; $-2 \leq SPI < -1.5$; $-1.5 \leq SPI < -1$; $-1 \leq SPI < -0.5$; $-0.5 \leq SPI < 0$; $0 \leq SPI < 0.5$; $0.5 \leq SPI < 1$; $1 \leq SPI < 1.5$; $1.5 \leq SPI < 2$; $SPI \geq 2$). As Table A6 shows, these monthly deviations over the same 5-year period do not show any significant results. We believe the reason for this is because short duration rainfall shocks, insofar as they cause short term income shocks, may allow for the possibility of consumption smoothing. A relatively dry month, if followed by a relatively wet month, may not lead to deprivation significant enough to detect long term impacts as are studied in this analysis.

Appendix 3. The ability of infrastructure to buffer the long-term impacts of drought

A3.1 Overview

In terms of the policy implications of our findings, an important aspect to consider is whether irrigation infrastructure may buffer households from the long-term impacts of drought on adult wealth. Thus, in this section, we investigate whether infrastructure may play a role in buffering women from drought exposure, and thus prevent drought from becoming destiny. Specifically, we investigate the role that upstream irrigation infrastructure plays in mitigating the impact of drought, at our standard drought threshold of SPI < −1.5. To isolate regions located within the command areas of irrigation facilities (where they would be expected to have the greatest mitigating effect), we focus on infrastructure located at a distance of between 25 and 50 km upstream from where the DHS respondent was born. This ensures that individuals are not within the catchment areas of dams, where evidence shows there may be negative impacts from increased water logging, soil salinity, and where the benefits of the dam would not reach (Duflo and Pande, 2007).

We first look at the impact of irrigation infrastructure within an OLS model. Being cognizant of the fact that the placement of irrigation facilities may be endogenous, we also test the impact using an instrumental variables approach.

A3.2 Data on irrigation infrastructure

The universe of large irrigation infrastructure facilities is from the Global Reservoir and Dam (GRanD) v1 dataset, from SEDAC (Lehner et al., 2011a, Lehner et al., 2011b). We only include dams which have either the main, major, or secondary purpose of irrigation. Using the remaining irrigation infrastructure facilities in GRanD, for each household, we estimate the number of large irrigation infrastructure for which the household falls into the command

Table A6
A semiparametric modelling of rainfall.

	(1)	(2)	(3)	(4)	(5)
	Wealth	Education	Height	Lacks agency	LBW child
Number of months of exposure in early childhood to SPI bins:					
SPI: <−2	−0.000371	−0.0182	−0.0113**	0.00124*	−1.41e−06
	(0.000674)	(0.0115)	(0.00521)	(0.000659)	(0.00132)
$-2 \leq$ SPI < −1.5	−0.000235	−0.000670	−0.00526	0.00104*	0.00108
	(0.000615)	(0.00989)	(0.00390)	(0.000575)	(0.00114)
$-1.5 \leq$ SPI < −1	−0.000565	−0.0135*	−0.00456*	0.000767*	0.000766
	(0.000411)	(0.00696)	(0.00255)	(0.000459)	(0.000757)
$-1 \leq$ SPI < −0.5	−0.000729*	−0.00635	0.00327	0.000238	−0.00128*
	(0.000420)	(0.00726)	(0.00255)	(0.000406)	(0.000762)
$-0.5 \leq$ SPI < 0	*Reference category*				
$0 \leq$ SPI < 0.5	0.000192	−0.00680	0.00505*	0.00109***	−0.000272
	(0.000412)	(0.00723)	(0.00265)	(0.000414)	(0.000704)
$0.5 \leq$ SPI < 1	−0.000489	−0.00510	−0.000190	0.000388	−0.000279
	(0.000414)	(0.00727)	(0.00265)	(0.000412)	(0.000756)
$1 \leq$ SPI < 1.5	0.000108	−0.00141	0.00518	0.000926	0.000994
	(0.000512)	(0.00880)	(0.00362)	(0.000590)	(0.000864)
$1.5 \leq$ SPI < 2	0.000363	0.0147	0.00699	0.000322	0.000717
	(0.000809)	(0.0119)	(0.00445)	(0.000909)	(0.00107)
SPI ≥ 2	0.00154	−0.0226	−0.00139	−1.37e−05	0.00202
	(0.00106)	(0.0155)	(0.00575)	(0.00110)	(0.00144)
Controls	Temperature t:t + 4; gridcell fixed effects; country X year fixed effects; birth-month fixed effects				
Number of observations	76,902	52,733	76,857	60,440	14,731
R2	0.331	0.174	0.556	0.304	0.147

Notes: Table shows results from estimating Eq. (1) via ordinary least squares (OLS). Each column displays estimates from a separate regression. The dependent variable in column 1 is wealth, in column 2 is education (in years), is column 3 is height (in cm), in column 4 is an indicator equal to 1 if the female respondent's husband/partner has the sole say in any household decisions, and 0 otherwise, and in column 5 is an indicator equal to 1 if any of the female respondent's children were born with below normal birthweight (<2.5 kg). In this specification, drought is measured as the number of months, over the early-life time period, where SPI fell into different bins of SPI severity. Standard errors are clustered at the country-year level, and are presented in parentheses. ***, **, * denote statistical significant at the 1%, 5% and 10% levels respectively.

area of; further details of this procedure and these data can be found in Damania et al. (2017). The GRanD dataset contains the year of dam construction – allowing for this variable to have a panel dimension. The year following construction is assumed to be the beginning year for operation the dam.

A3.3 Methodology

We analyze the long-term impact of being born in the command area of a dam, as well as the role that irrigation infrastructure play in potentially providing a buffer during dry spells (when rainfall amounts are significantly below average). To do this, we include a variable which indicates the number of upstream irrigation infrastructure from the household, as well as interacting this variable with cumulative exposure to drought in early childhood. The sign and significance on this coefficients will tell whether the presence irrigation infrastructure can impact long run wealth, and buffer the harmful effects of dry shocks. The specification for this model is:

$$Y_{ijt} = \alpha + Irrig_{ijt} + Drought_{ijt} + Irrig * Drought_{ijt} + Year_t \times Country_c + \delta_P + \vartheta_M + AvgMonthlyTemp_{jt} + \varepsilon_{ijt} \quad (2)$$

The outcome variable, Y_{ijt}, is adult wealth of respondent i, born in location j, at time t. The number of upstream irrigation infrastructure facilities within a 25–50 km radius is given by $Irrig_{ijt}$, and the $Irrig * Drought_{ijt}$ term represents the role that irrigation infrastructure facilities play in mitigating the effects of drought in early childhood on adult wealth. Unlike Eq. (1), this specification does not include grid-cell fixed effects as there is relatively little variation over time in the number of upstream irrigation infrastructure facilities within a given grid cell. Thus, the inclusion of grid-cell fixed effects would absorb the impact of irrigation infrastructure facilities, therefore, grid-cell fixed effects are replaced by province fixed effects (δ_P).

Duflo and Pande (2007) note that it is unlikely that OLS estimates of the role of irrigation infrastructure facilities will provide unbiased results as dam construction is likely to be endogenous; if irrigation infrastructure facilities are constructed in wealthier regions (which is not unlikely) there may be reverse causality between dam construction and wealth, furthermore, dams are likely to be constructed where they are expected to have the greatest impact. To address this potential endogeneity, we follow Duflo and Pande (2007) and Strobl and Strobl (2011) and instrument for the presence of irrigation facilities using data on the geography of their construction. Specifically, we predict the likely number of irrigation infrastructure facilities constructed within the 25–50 km threshold using data on the river gradient and the river length within this threshold, and a time trend. In constructing the river-length variable, the USGS Hydrosheds River Database is used to obtain a global shapefile of rivers. River length provides a measure of river access – an important predictor of the construction of irrigation facilities. As this captures river access in the 25–50 km buffer, it should be uncorrelated with income of the household. The river slope instrument is based on the share of rivers within the 25–50 km threshold with a slope of 1.5–3% as this is the slope gradient that Duflo and Pande (2007) found to be the best predictor of irrigation infrastructure construction. Finally, a time trend is used to capture the increasing number of large dams being built in these countries over time.

Thus, in our IV estimates, the $Irrig_{ijt}$, variable is replaced by its predicted values ($\widehat{Irrig_{ijt}}$) from the first-stage results. We estimate the model using two-stage least squares.

A3.4 Results

Table A7 shows the results from estimating Eq. (2) using OLS (column 1) and two-stage least squares (column 2). According to the OLS results, the presence of upstream irrigation infrastructure

Table A7
The role of irrigation infrastructure in mitigating the effects of drought.

	(1) OLS model	(2) IV model
Number of upstream dams	0.096***	0.642***
	(0.015)	(0.235)
Cumulative drought exposure	−0.035*	−0.107**
	(0.020)	(0.052)
Number of upstream dams X drought exposure	−0.065	1.215
	(0.086)	(0.972)
Controls	Temperature t – t + 4; province fixed effects; country X year; birth-month fixed effects	
Number of observations	76,912	58,102
R2	0.228	0.156

within the 25–50 km buffer around the time of birth increases female adult wealth. However, the OLS results also show that, while cumulative drought exposure in early life decreases adult wealth, irrigation infrastructure does not significantly buffer the women from these negative effects.

The two-stage least square results confirm that the presence of irrigation infrastructure is positively associated with wealth, and that cumulative exposure to drought in early childhood negatively impacts adult wealth. However, similar to the results from the OLS model, the IV results also show no evidence that irrigation infrastructure mitigates the impact of drought. There is one important caveat to make here: for households in our sample, there are relatively few irrigation facilities present within the 25–50 km buffer zone, with the average value being less than one, so it is difficult to estimate a meaningful statistical impact.

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